

9-second gridded continental biodiversity analyses for Australia: November 2014

Short summary

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This document summarises in plain language the methods applied to generate gridded Australian analyses of biodiversity, climate change and land use from GDM transformed grids.

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1 Biodiversity Analyses

Biological data were compiled from the Atlas of Living Australia and the ANHAT data, and filtered to correct for invasive species, incorrect records and duplicate names for the same species. Best-available environmental data at 9 second resolution across Australia were compiled, including climate, substrate and landform variables. Climate surfaces were calculated for both present (1990:1976-2005) and future (2050:2036-2065) climates using a consistent methodology (section 2). Generalised Dissimilarity Modelling was used to fit the dissimilarity in species composition to the change in environment, allowing the transformation of each selected environmental layer. GDM transformed environmental grids are in units of ecological distance (ΔE), such that the difference in value between any two grid cells (i,j) for a given layer (x) represents the contribution to ecological distance between the two cells for that layer. By summing the absolute differences within all the transformed layers ($|x_i-x_j|$), we obtain the modelled ΔE between the two cells . By applying a negative exponential transformation, we can then calculate the modelled Sorenson compositional similarity (s_{ij}) between the two cells. The offset, o is ignored for analyses working across time periods.

$$s_{ij} = e^{-\Delta E} = e^{-\left(\sum_{x=1}^{x=N} |x_i - x_j| + o\right)}$$
 [1]

Taking two stacks of transformed grids, one for the present and one for the future, we can compare each cell in either of the time points with all the cells in both its own and the alternative time point. In practice, although the calculation must be applied to all cells to generate a map, the scale of the calculations requires that sampling is applied to the cells to which each cell is compared. This comprised a moving half-cauchy distributed radial sample of 30,000 cells within a 100km radius and a global sample of 30,000 cells across the remainder of the continent.

The modelled compositional similarity can be used to scale environmental change. However, under climate change, in situ persistence of species, local adaptation of species and limited dispersal will act to limit the loss of species from a site. This is offset by the potential inability of suitable new species to colonise the site. In practice, therefore, we do not necessarily expect this ecological change to be realised.

S: Potential degree of ecological change: By calculating the similarity between the same cell at two points in time, using equation 1, we obtain the projected similarity as a function of changing climate.

DS: Disappearing ecological environments: The state of each cell in the present is compared with the future state of all cells. The similarity of the most similar cell is recorded, wherever it is found

$$DS_{i} = \max_{i=1}^{j=n} \left(s_{ii}^{present_future} \right)$$
 [2]

NS: Novel ecological environments: The state of each cell in the future is compared with the present state of all cells. The similarity of the most similar cell is recorded, wherever it is found

$$NS_{i} = \max_{j=1}^{j=n} \left(s_{ij}^{future_present} \right)$$
 [3]

In combination these three metrics can be used to describe the character of change at a site, from low change in a novel direction, to high change towards a more familiar environment. However, it is not possible to directly ascertain what a future environment would look like from these metrics, which would require a map for each grid cell.

Change in area of similar ecological environments

The total area of ecological environments similar to any grid cell (A) can be calculated as the sum of similar ecological environments (i.e. the sum of pairwise similarities). This may also be multiplied by a habitat condition (h) here taken as a continuous 0 (cleared natural areas) to 1 (extant) index of intactness of habitat.

$$A_i = \sum_{j=1}^{j=n} s_{ij} h_j$$
 [4]

This area can be calculated for all land under present ecological environments to provide a baseline area, against which any change can be measured.

$$A_i^{pristine} = \sum_{j=1}^{j=n} s_{ij}$$
 [5]

The change in area of similar ecological environments under climate change can be calculated by

$$C_{i} = \frac{A^{future_pristine}}{A^{current_pristine}} = \frac{\sum_{j=1}^{j=n} s_{ij}^{future}}{\sum_{j=1}^{j=n} s_{ij}^{present}}$$
[6]

The effects of current land clearing on biodiversity (through change in area of similar ecological environments can be calculated based on a mask of cleared natural areas compiled within CSIRO from latest Department of the Environment data (25m resolution version of Australian Government Department of the Environment, 2014).

$$C_{i} = \frac{A^{current}}{A^{pristine}} = \frac{\sum_{j=1}^{j=n} s_{ij} h_{j}}{\sum_{i=1}^{j=n} s_{ij}}$$
[7]

Or the combined effects of future climate and land use change as

$$C_{i} = \frac{A^{future_pristine}}{A^{current_pristine}} = \frac{\sum_{j=1}^{j=n} s_{ij}^{future} h_{j}^{counterfacual}}{\sum_{j=1}^{j=n} s_{ij}^{present}}$$
[8]

2 Calculation of 9s gridded climate and projected climate change surfaces for Australia

Climate surfaces for the present were based on the ANUCLIM 6.1 (Xu and Hutchinson, 2011) 30 year average climate surfaces for Australia, with elevational lapse rate correction applied over the 9s GEODATA digital elevation model (Hutchinson et al , 2008). Radiative correction derived from the same DEM was applied to radiation and maximum temperature before calculation of evaporation, using the CSIRO TerraFormer software. Projected future climates were generated by applying within-model changes (e.g. MIROC5 2036-2065 – MIROC5 1976-2005) calculated at the native general circulation model grid resolution to these current surfaces, using ANUCLIM 6.1 prior to radiative adjustment. Summary statistics for each variable were then calculated (Figure 1).

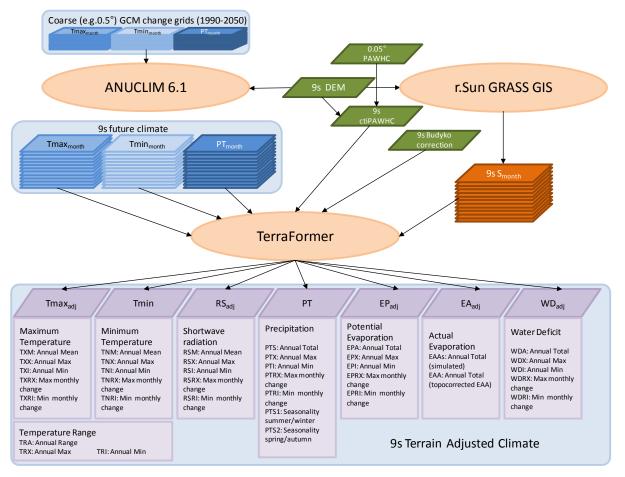


Figure 1: Calculation of present and future climate surfaces using a consistent approach for all time points.

An approach was taken which minimises the data requirements for projection of climate, whilst maintaining consistency of calculation across time points. We followed Allen *et al.* (1998) FAO 56 p 76 "Calculation procedures with missing data" and Example 20 p77-78, which outlines standard procedures for the estimation of Ep (ET_0) as a function of monthly average daily maximum and minimum temperatures. Due to concerns as to the validity of derived or projected wind and humidity variables, we substitute the Priestley-Taylor formulation for the Penman-Monteith equation. Whilst FAO 56 Eq 50 (Hargreaves) is used for the estimation of Rs, we used the Samani (2000) derivation of KT (k_{Rs}) to deal with geographical variation in KT. Once Rs has been estimated from diurnal temperature range, we adjust both radiation and

maximum temperature using the ratio *S* (shaded inclined radiation/unshaded flat surface radiation, calculated in GRASS using the r.sun routine) following Wilson & Gallant (2000).

All variables *Tmax, Tmin, Ppt, Rs, Ep, Ea* and *WD (Ppt-Ep)* are calculated monthly. These are then summarised as: Annual total or mean, Maximum monthly value, Minimum Monthly value, Maximum rate of month to month change and Minimum rate of month to month change. Interactions between variables such as temperature of the wettest month are avoided for climate change sensitivity reasons.

Potential Evaporation (Ep)

Humidity data is difficult to come by, since it is partly a function of local surface moisture. Estimates of humidity as a function of temperature are very unreliable for much of the tropics. Consequently we would be forced to make extreme assumptions about humidity in order to properly incorporate it into the Penman-Monteith formula.

Wind data is similarly sparse, but is also subject to topographic funnelling leading to strong local heterogeneity. Whilst this can be modelled for the present, the data has high commercial value and is not readily available. Projections of future wind by GCMs are non-standard and subject to local topographic interactions which would require further modelling. The use of a uniform 2m^{-s} wind speed effectively removes the contribution of wind to the Penman-Monteith formula.

We therefore apply the purely energy-driven Priestley-Taylor formula (Fig2) (e.g. Wilson & Gallant 2000), which requires as inputs *Tmax*, *Tmin*, *Tdew* and *Rs*. We estimate *Tdew* as *Tmin* which has minimal implications in the Priestley-Taylor approach. In the current algorithm, *Rs* is derived from diurnal temperature range to ensure consistency between variables at any site/time point.

Actual Evaporation (Ea)

Two actual evaporation products are produced, a raw modelled output and a remotely sensed adjusted output.

a) Modelled output (Ea_{mod}). Ea is calculated monthly using the Budkyo framework (Budkyo 1958,1974, Choudhury, 1999) in a bucket model (Pike, 1964) as $E_a = \frac{(V+P).ET_p}{\left[(V+P)^n+ET_p^n\right]^{\frac{1}{2}/n}}$ where V is stored water, P,

precipitation and recorded as an annual sum. The bucket size *Vmax* is calculated as a TWI corrected PAWHC value, according to Claridge *et al.* (2000).

b) Remote sensing corrected Ea_{corr} . Remote sensed Ea_{rs} in the present is taken as truth. The offset on the Phi axis of the Budyko framework between the modelled Ea_{mod} and Ea_{rs} in the present is used to correct all projected Ea_{mod} surfaces (Fig 3). By definition this results in $Ea_{corr} = Ea_{rs}$ in the present. The calculation is standard for all time points and scenarios.

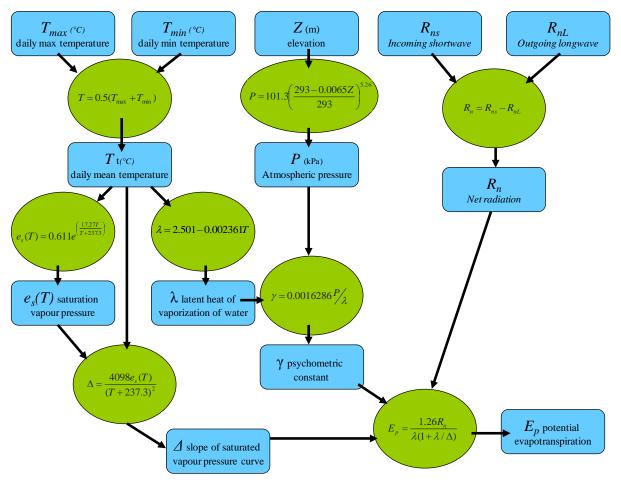


Figure 2: Calculation of *Ep* using the Priestley-Taylor approach. See Allen *et al* (1998) for further details.

Future climate scenarios

Future climate was calculated following the ANUCLIM 6.1 approach to generate monthly Maximum and Minimum Temperatures and Precipitation (Xu & Hutchinson 2013). Monthly change grids for these variables were calculated as within Generalised Circulation Model changes for long term averages centred on the relevant time points. Data were extracted from the CMIP5 database (Taylor et al., 2013) and calculations applied in the native grid resolution.

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\Delta Tmax_{month} = Tmax_{month} \ (projected \ 2036-2065) - Tmax_{month} \ (1976-2005)
\Delta Tmin_{month} = Tmin_{month} \ (projected \ 2036-2065) - Tmin_{month} \ (1976-2005)
\Delta PT_{month} = 100*[PT_{month} \ (projected \ 2036-2065) - PT_{month} \ (1976-2005)] / PT_{month} \ (1976-2005)
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Two future climate models were initially examined, using the RCP 8.5 high emissions future consistent with current trends:

The CanESM2 model

Chylek P, Li J, Dubey MK, Wang M and Lesins G (2011) 'Observed and model simulated 20th century Arctic temperature variability: Canadian Earth System Model CanESM2', ATMOSPHERIC CHEMISTRY and PHYSICS DISCUSSIONS **11**, 22893—22907 doi:10.5194/acpd-11-22893-2011

The MIROC5 model

Watanabe M, Suzuki T, O'ishi R, Komuro Y, Watanabe S, Emori S, Takemura T, Chikira M, Ogura T, Sekiguchi M, Takata K, Yamazaki D, Yokohata T, Nozawa T, Hasumi H, Tatebe H and Kimoto M (2010) 'Improved Climate Simulation by MIROC5. Mean States, Variability, and Climate Sensitivity', JOURNAL of CLIMATE **23**(23), 6312-6335, doi:10.1173/2010JCLI3679.1

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http://www.environment.gov.au/metadataexplorer/explorer.jsp

Budyko, MI (1958) The heat balance of the earth's surface, US Dept. Of Commerce, Washington.

Budyko, MI.(1974) Climate and life. Academic Press, New York.

Choudhury, BJ (1999)Evaluation of an empirical equation fro annual evaporation using field observations and results from a biophysical model. J. Hydrology 216: 99-110.

Claridge J, Williams KJ, Storey RJL (2000) Creation of the South-East Queensland depth index rescaled using CTI, Brisbane, Enhanced Resource Assessment 2000-05. A JVAP project QDN3A Technical Report. Queensland Department of Natural Resources.

Hargreaves, GH, and Samani, ZA (1982). "Estimating potential evapotranspiration." J. Irrig. Drain Eng., 108(3), 225–230.

Hutchinson, M, Stein, J, Stein, J, Anderson, H & Tickle, P (2008) GEODATA 9 second DEM and D8. Digital elevation model version 3 and flow direction grid. Gridded elevation and drainage data. Source scale 1:250 000. User guide (3rd ed). 3 edn, (Fenner School of Environment and Society, the Australian National University and Geoscience Australia, Australian Government).

Pike, JG (1964) The estimation of annual run-off from meteorological data in a tropical climate. Journal of Hydrology, 2: 116-123.

Samani, Z (2000). "Estimating solar radiation and evapotranspiration using minimum climatological data (Hargreaves-Samani equation)." J. Irrig. Drain Eng., 126(4), 265–267.

Taylor KE, Stouffer RJ and Meehl GA (2012) 'An overview of CMIP5 and the experiment design' BULLETIN OF THE AMERICAN METEOROLOGICAL SOCIETY 93(4), 485-498 doi:10.1175/BAMS-D-11-00094.1

Wilson JP, Gallant JC (2000) Secondary topographic attributes. In: Terrain Analysis: Principles and Applications. (eds Wilson JP, Gallant JC) pp Page. New York, John Wiley & Sons.

Xu, T & Hutchinson, M. ANUCLIM Version 6.1 User Guide (2011). (The Australian National University, Fenner School of Environment and Society).

Xu, T. & Hutchinson, M.F. (2013) New developments and applications in the ANUCLIM spatial climatic and bioclimatic modelling package. Environmental Modelling & Software, 40, 267-279.

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